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POSITION-LIMIT DESIGN FOR THE CSI 300 FUTURES MARKETS

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Position-Limit Design for the CSI 300 Futures Markets

Abstract. The aim of this paper is to find the optimal level of position limit for the Chinese Stock Index (CSI) 300 futures market. A small position limit helps to prevent price manipulations in the spot market, thus able to keep the magnitude of instantaneous price changes within policy makers' tolerance range. However, setting the position limit too small may also have negative effects on market quality. We propose an artificial limit order market with heterogeneous and interacting agents to examine the impact of different levels of position limit on market quality, which is measured by liquidity, return volatility, efficiency of information dissemination and trading welfare. The simulation model is based on realistic trading mechanism, investor structure and order submission behavior observed in the CSI 300 futures market. Our results show that based on the liquidity condition in September 2010, raising the position limit from 100 to 300 can significantly improve market quality and at the same time keep maximum absolute price change per 5 seconds under the 2% tolerance level. However, the improvement becomes only marginal when further increasing the position limit beyond 300. Therefore, we believe that raising the position limit a moderate level can enhance the functionality of the CSI 300 futures market, which benefits the development of the Chinese financial system.

Key words: Position limit, stock index futures, agent-based modeling, market quality.

JEL Classification: G14, C63, D44

1. Introduction

Chinese economy is growing rapidly. It has already become the second largest economy in the world. However, the Chinese financial markets remains underdeveloped and its functionality needs further improvement compare to other international financial markets. The Chinese Stock Index (CSI) 300 futures was introduced on April 16, 2010 in an effort to improve the country's financial system. The CSI 300 futures allows investors to take short positions on futures which provides a hedge against the risk arising from the Chinese stock market. The introduction of the futures market was considered a milestone, which would bring the Chinese financial market into a new era.

However, during the first phrase after its introduction, the CSI 300 futures market has not performed well because many of the market participants are individual investors who supplied little liquidity to the market. One possible reason is the conservative design of the position limit[1]. To ensure that the CSI 300 futures market launches safely and to prevent market manipulation, the initial position limit of the CSI 300 futures market is set to 100 contracts, which could be insufficient for the institutional investors[2]. The low position limit of 100 could potentially restrain the institutional investors from taking trading optimally to provide sufficient liquidity to the market, which results in low trading volume and order depth. Thus, the investors CSI 300 futures ultimately suffers from the poor market quality. The policy maker faces the trade-off between improving market quality (by increasing the position limit) and the prevention of market manipulation (by keeping a low position limit). The question is: What is the optimal level for the position limit?

This paper proposes an agent-based model to simulate changes in market quality given different levels set for the position limit. The market design and investor structure used in the model is chosen to best mimic the CSI 300 futures market. However, first, an empirical study is conducted and finds that a position limit of 371 should be sufficient if the policy maker wants to prevent manipulation and keep instantaneous price change within the 2% bound. Then, simulation results from the agent-based model show that when the position limit increases from 100 to 300, market quality improves significantly. However, increasing the position limit beyond

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[1]A position limit is the maximum unilateral position of a certain contract allowable holding by members/customers. Security exchanges set position limits mainly for two reasons. First, to prevent the market manipulation by large institutions and second, to prevent the risk of a minority investor group holding a large unilateral position that might cause price fluctuations and defaults to spread into the entire market.

[2]Suppose the CSI 300 is at 2,000, as the value of one index point is 300 CNY, one speculative account can only conduct trades within the 60 millions CNY limit, which is rather low comparing to the market capitalization of the CSI 300, which is more than 13,000 billions.

300 shows much less improvement in market quality. Furthermore, our simulation results also show that increasing the position limit to 300 does not lead to absolute price changes of more than 2%. Therefore, we find that a position limit of 300 is close to being optimal for the CSI 300 futures market. This paper also shows that agent-based modelling can be very useful for the policy makers who needs to make a decision in a complex environment (such as the financial system) and may have multiple objectives.

To provide some background information to understand why the position limit in the CSI 300 futures market is initially set to such a conservative level at 100, we first briefly review some of the important market events which occurred before the introduction of the CSI 300 futures market. The most serious incidence of market manipulation is the so-called "3.27" treasury futures incident, which occurred on March 27, 1995. Before the incident, Wanguo Security (WS)[3] held a long position of approximately 2 million contracts in the treasury futures, and the opposite side of trade is Zhongjingkai Security (ZS) which held a short position of similar size. Both companies were highly leveraged, a small price change could send either company to bankruptcy. In the afternoon of March 27, 1995, when the China Ministry of Finance decided to give the finance discount to the treasuries, the futures price raised up quickly and the loss of WS was more than 6 billion CNY, which is 5 times of the market value of WS[4]. However, WS manipulated the market and sold huge orders to push the market price down, the last sell market order had a quantity of 7.3 million[5]! These crazy behaviors made the Chinese treasuries futures market to close down since then. The "3.27" treasuries futures incident lead to the close down of the treasury futures market and delayed the introduction of a stock index futures market for 15 years. Hence, when the CSI 300 futures market was introduced, there were serious concerns about market manipulation, which lead policy makers to set the position limit to a very conservative level[6].

Other international stock index futures markets also use position limits. For example, the position limit is 20,000 for the S&P 500 and 10,000 for the Nikkei 225. However, some stock index future markets have no position limit, such as the Mini Dow stock index futures and the FTSE 100 stock index futures. Comparing to these markets, the position limit for CSI 300 futures is very conservative. Intuitively, position limits depend on market conditions. Some studies argue that position limits

[3]The biggest security company in China at that time.

[4]WS did not go bankrupt because profit and losses were only realized when the position is closed.

[5]The amount of this order is 146 billion CNY. There was no margin requirement to prevent WS from opening such a huge short position.

[6]Actually, in the pre-introduced phase (simulation trading phase), the position limit was set to 600, but then it was adjusted to 100 when it was introduced.

are not necessary. Gastineau (1991) and Telser (1993) argue that the position limits set by the SEC in the US is not sufficient to prevent manipulation. Grossman (1993) suggests that position limits in the futures markets simply move transactions from local markets to foreign markets, which does not help to prevent market manipulations. However, several research support the idea that position limits place restrictions on market manipulation. Kyle (1984) develops a theoretical model of a commodity futures market, and shows that position limits can reduce market manipulation. Kumar and Seppi (1992) conduct a sensitive analysis of market manipulation with two-stage asymmetric information in a cash-settled futures contract market. They find that market manipulation has a significant impact on liquidity. Therefore, the some of the above literature support the idea that position limit is helpful in the prevention of market manipulation, however they do not provide ways to find the optimal level of position-limit given certain market conditions.

Dutt and Harris (2005) propose a theoretical model for setting an optimal position limit in a cash-settled futures market. They argure that surveillance and the detection of market manipulation is difficult, therefore the regulator could set a position limit low enough such that instantaneous price changes are within a tolerable range. The authors then examine prudent position limits among the U.S. financial derivation markets. However, they do not study the influence of position limits on market quality including liquidity, volatility, and pricing efficiency. In order to examine impact of position limits on these market-quality indicators, one needs to model the trading behavior of the investors and to the way position limits affect the trading strategies used. It is a difficult task to model trading behaviour in a limit order market, which employs a continuous double auction trading mechanism and allow traders use both market and limit orders. Theoretical models often lose analytical intractability, as pointed out by Goettler, Parlour and Rajan (2009): " *A model that incorporates the relevant frictions of limit-order markets (such as discrete prices, staggered trader arrivals, and asymmetric information) does not readily admit a closed-form solution."* As a result, Goettler et al. (2009) use numerical methods to solve for equilibrium. Even then, Goettler et al. (2009) needed to assume that the uninformed traders' order submission to a large extent is determined by a exogenously private value and the traders can not learn from historical market data, which limits the applicability of their model to real markets.

An alternative way is to use agent-based models. The advantages of agent-based models are pointed out by Dawid and Fagiolo (2008), *"The ability of ACE (agent-based computational economics) models to capture explicitly the relationship between structured interaction of heterogeneous individuals and the emerging patterns at the macroeconomic level, and to incorporate different types of boundedly rational individual behavior ".* More importantly, in comparing agent-based models with neoclassical models, they further point out that: *"Political decision makers might be more willing to trust findings based on rather detailed simulation models where they see a lot of the economic structure they are familiar with than in general insights obtained in rather abstract mathematical models "*. Recently, some progress has been made in applying agent-based models for policy design. For example, in stock index futures markets, Xiong, Wen, Zhang and Zhang (2011) analyze the impact of different investor structures on market volatility in an artificial stock index futures market and illustrate that the risk-diffusing mechanism in the cross-market structure. Moreover, Wei, Zhang, He and Zhang (2013) constructs an artificial limit order market model with a continuous double auction trading mechanism and study the efficiency of information-dissemination through the learning ability of the uninformed traders. Furthermore, Wei, Zhang, Xiong and Zhao (2014) set up an artificial stock index futures market based on the characteristics of the CSI 300 futures market and analyze how the minimum tick size affect market quality.

One of the drawbacks of agent-based models is the large number of parameters in the model and lack of efficient methods for determining the values for these parameters. To overcome this problem, we combine empirical analysis into our agent-based model through two steps. First, following Dutt and Harris (2005), we use empirical data from the CSI 300 futures market to find the prudent position limits for different tolerance levels for the instantaneous price changes. Then, we use the data on investor types and order submission to determine parameter value for the agent-based model and analyze the simulation results to examine whether increasing the position limit helps to improve market quality for the CSI 300 futures market.

The paper is organized as follows: Section 2 uses the emprical data from CSI 300 futures market and follows Dutt and Harris (2005) to find a suitable position limit to keep instantaneous price changes within a given tolerance range. Section 3 presents the agent-based computational model and describe the setup of the market and the order submission rules. Section 4 evaluates the impact of increases in the position limits on efficiency of information dissemination, volatility and liquidity. Section 5 concludes.

2. Prudent position limits for the CSI 300 futures Market

In practice, it is very difficult to detect manipulations and to distinguish manipulative activities and legitimate speculative activities. Dutt and Harris (2005) argue that surveillance and prosecution are inadequate to control market manipulations, and position limit is an alternative way. They assume that if instantaneous price change is no more than the regulator's tolerance level, the regulator would not spend resources to distinguish the manipulative trades from speculative trades. As such, manipulators would be active in the market[7]. The prudent position limit can be generated from the analysis of the optimal behavior of a manipulator. For a given tolerance level for instantaneous price changes, the manipulator's objective is to maximize his profit from trades. It is assumed that price is a linear function of aggregate demand, the prudent position limit is set such that it would not be optimal for the manipulators to make the price change more than the tolerance level of the regulator. Following Dutt and Harris (2005), we derive the prudent position limit as showed in Equation 1, see the derivation details in Appendix A.

$$\theta^* = \frac{DK}{500m\varepsilon \sum_{i=1}^{300} \psi_i \omega_i}, \tag{1}$$

where θ^* is the prudent position limit, D is the sum of the value-weighted constituent stocks' capitalization in the initial period, k is the regulator's tolerable price change, m is the contract multiplier, ε is an elasticity measuring the market illiquidity, ψ_i is the capitalization-value-weight of the ith component stock, and ω_i is the proportion of the tradable shares of the ith component stock.

According to Equation 1, we calculate prudent position limits for the CSI 300 futures. Using data from the Guo Tai'an Database[8], we find $D = 4,700,862,800$ CNY in the base period (Dec. 31, 2004), and $\sum_{i=1}^{300} \psi_i \omega_i = 0.009$. The contract multiplier $m = 300$. The regulator's tolerable price change $k\%$ is set to 1% for a low tolerance level and to 2% for a high tolerance level[9].

Dutt and Harris (2005) evaluate ε from the transaction cost prediction models of ITG and Goldman, which focus on U.S. markets. Instead, we evaluate ε by the market impact cost in the CSI 300 futures market based on the method in Almgren, Thum, Hauptmann and Li (2005). We choose one month high-frequency transaction data to estimate the market impact cost and the results are shown in Table 1. The data of the main contract IF^{1009} is from August 23 to September 15 in 2010[10]. There are in total of 18 trading days' data with 5-second time-intervals, corresponding to 51,876 records in 18 days and 2,882 records per day[11].

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[7]They may even act like speculators.

[8]Guo Tai'an is the biggest data provider for Chinese financial markets.

[9]Dutt and Harris (2005) set $k\%$ to 3%. However, due the more serious concerns of manipulation in the Chinese financial markets, we set the tolerable level for price changes to more conservative levels.

[10]We exclude three days of one month data: August 20, the first day that IF^{1009} became the main contract and its volume has changed a lot; September 17, the delivery day, and September 16, the day prior to delivery due to small trading volume.

[11]We also use the same period data including trading frequency, order profit, and order size, to analyze investor behaviors. The statistical analysis of these indicators provides a basis for the parameters setting of our agent-based model, see detail in the next section.

Table 1 shows the value of ε for different quantiles. Our results are similar to those in Dutt and Harris (2005). A larger ε means that the market is more illiquid. We choose the 50% quantile as the normal state for market liquidity and 90% quantile as the worst state for market liquidity.

Quantile	10%	25%	50%	75%	90%
ε	144.6	162.3	187.8	230.1	312.6

TABLE 1. Illiquidity elasticity estimates by market impact cost.

Now we can calculate the prudent position limits according to Equation 1, the results are reported in Table 2.

Illiquidity	$k\%=1\%$	$k\%=2\%$
$\varepsilon=187.8$	185	371
$\varepsilon=312.6$	111	223

TABLE 2. Prudent position limits with different tolerable price change and illiquidity.

Table 2 shows that if the tolerable level is 1% and the market is very illiquid ($\varepsilon = 312.6$), the prudent position limit is 111, which is close to the initial position limit of the CSI 300 futures market. However, if the Chinese regulators are willing to tolerate a 2% instantaneous price change, under the normal liquidity state, prudent position limit can be as high as 371. The question is whether increasing the position limit for the CSI futures market can significantly improve its market quality. To address this question, we conduction a simulation analysis using an agent-based model in a limit order market.

3. An agent-based computational model

This section first provides the architecture of the agent-based computational model, including tradable assets, market design, investor types, forecasting rules, order size, and order-submission rules. Then we calibrate the parameters to create an artificial CSI 300 futures market (ACFM) and set different position limits suggested by previous studies in Section 2 to examine its impact on market quality using analysis methods.

3.1. Fundamental Value.

The pricing theory of stock index futures implies a lead-lag relationship between futures and underlying assets. Let v_t be the fundamental value of a stock index futures with initial value v_0. In real markets, if the futures price deviates from its fundamental value, arbitragers will take short positions to push the futures price back to its fundamental. Due to the no-short-selling in the Chinese underlying markets, investors can only do cash-and-carry arbitrage by shorting futures and take long position in the underlying stocks when the futures price is above its fundamental value. Therefore, we choose the ceiling of the cash-and-carry arbitrage of the CSI 300 futures as fundamental value. Cash-and-carry requires the arbitrager to borrow at the market interest rate for a time horizon that matches the maturity of futures contract, in order to take long positions in the underlying stocks, and then take a short positions in the futures. The cost of cash and carry provides a ceiling for the futures price, which we call the fundamental price. A detailed derivation of the fundamental price is provided in Appendix B, which incorporates interest rate, transaction cost, market impact cost, dividend of underlying stocks, margin ratio and the time to maturity as key determining factors of the fundamental price. Due to the transaction cost, the ceiling is always higher than the futures theoretical value, which is $e^{rT}S_t$. The difference between the ceiling and the theoretical price decreases when it is closer to maturity. As mentioned in Section 2, we use 5-second-intervals data of the CSI 300 index from August 21 to September 15 in 2010 to calculate the fundamental value. We generate a time series of fundamental values with 51,876 records, which we then use to run simulations in the artificial CSI 300 futures market.

3.2. **Market design.** To mimic the trading in the CSI 300 futures market, we employ a continuous double auction trading mechanism that enables a trader to submit both limit and market orders, which are listed and matched in an electronic order book. The order book is emptied out at the end of every trading day (practice used in the CSI 300 futures market). During one trading period (5 seconds), there can be several or no transactions. The market price p_t is the last transaction price at time t. If there are no transactions at time t, then we assume $p_t = p_{t-1}$. The initial market price $p_0 = v_0$. The transaction cost μ is set to 0.015% per transaction and the minimum tick size is set to 0.2 CNY. Furthermore, initially we set the position limit to 100 which is the same with the initial position limit in the CSI 300 futures market. To we increase the position limit to higher level to see whether market quality significantly improves.

3.3. **Investor types and structure.** We consider an asymmetric-information framework for the agent-based model, that is, a certain proportion of the investors have private information about the future fundamental value. For example, large institutional investors might know more about the fundamental value because of better information gathering abilities. The trading strategies of the informed and uninformed traders have different characteristics. Menkhoff, Osler and Schmeling (2010) find that informed traders trade more actively than uninformed traders. Wei et al.

(2013) find that informed traders have higher trading rate and make more profit than the uninformed traders when the information is short-lived.

Based on the high-frequency trading data of IF^{1009} on September 6, 2011, we identify seven different ranges for investors' trading frequencies, statistics are shown in in Table 3. Table 3 classifies the investors into four types based on their trading frequency and order profit, and transaction quantity in the CSI 300 market data. It shows that the investor whose trading frequency is higher than 135 gains the most profit on the day. These investors trade every 2 minutes on average, we call them *informed traders* with a market proportion of 3.3%. The second group is called *intelligent traders* with an average trading frequency of 80 per day, their order return rate is close to zero. They trade on average every 5 minutes and consists of 6.4% of the market. Traders with lower trading frequencies has lower order profits. The *simple traders* make up 80.1% of the market, however their order return is on average between −0.0389% and −0.0331%. The last groups is called *liquidity traders* who traded once on the day, their proportion of the market is 10.1% and their orders made an average loss of −0.1009%. Therefore, it seems from the data that informed traders tend to trade more frequently and make profits from traders with lower trading frequencies such as the simple traders and liquidity traders. Of course, we recognize that this is only one trading day, however similar pattern exists for other trading days in the similar time period.

Type	Range of f	Population	Proportion	Average of f	Order return rate
Informed traders	$f \geq 270$	194	3.3%	417	0.0447%
	$135 \leq f < 270$	279		187	0.0317%
Intelligent traders	$54 \leq f < 135$	915	6.4%	80	-0.0002%
Simple traders	$27 \leq f < 54$	1580	80.1%	37	-0.0331%
	$9 \leq f < 54$	4140		15	-0.0351%
	$2 \leq f < 9$	5673		4	-0.0389%
Liquidity traders	$f = 1$	1428	10.1%	1	-0.1009%

Table 3. The statistics are based on the high-frequency data of IF^{1009} in September 6, 2011. f is the trading frequency per day (270 minutes). The order return rate r_o^i of trader i is equal to $r_o^i = (p_o^i - p_c)/p_c$ for sell order, and $r_o^i = (p_c - p_o^i)/p_c$ for a buy order, where the p_o^i is the order's transaction price, and the p_c is the closing price on September 6, 2011. This is an approximation of investors' profit since we can not get data of investors' actual profit due to the privacy protection issues.

The information lag time τ is set according to the lead-lag relationship between the stock index futures and the spot price. *Sinolink Securities* estimates that it is most likely that CSI 300 futures price leads spot price for approximately 2 minutes[12] meaning that the private information in the stock index futures market releases to the spot markets after 2 minutes, so we assume that the uninformed traders acquire the fundamental value with lag of $\tau = 2$ minutes.

The investor structure setting is based on the statistical analysis of the CSI 300 futures market. The number of investors who enter into the market is about 14,200 per day. However, due to limited computing power, we set the number of investors to 284, which is about 1/50 of the actual population. Number of informed, intelligent, simple, and liquidity traders are adjusted accordingly to be 10, 18, 228, and 28 respectively.

We assume that investors arrive at the market following a Poisson process with intensity ϕ_i. The value of ϕ_i is set to 0.82, 0.45, 0.09, 0.008 for informed, intelligent, simple, and liquidity traders respectively, according to the statistics of the CSI 300 futures market. There could be several traders entering the market in the same time period t, in which case we randomize their time priority following an uniform distribution. Therefore, the precise time when a particular investor enters the market is given by t' of period t. When an investor enters the market, he cancels any unexecuted limit order and submit a buy/sell order of size $|q_t^i|$, a buy (sell) order would lead to a positive (negative) value for q_t^i. As it will be explained later, we use the empirical probability distribution of the submitted order size to determine the distribution of $|q_t^i|$.

3.4. **The investor forecasting rules for fundamental value.** We assume that all investors believe that the futures price will converge to its fundamental value. Therefore, investors make forecasts $p_{t'}^i$ about the fundamental value. The forecasting rules of informed traders, intelligent traders, simple traders, and liquidity traders are given as follows:

(1) Informed traders almost know the fundament value, however their forecast is contaminated by a random bias ξ, which follows a truncated standard normal distribution between -0.01 and 0.01. We assume that each time an informed trader make a forecast, there is a 10% chance for a forecasting bias to occur. The forecasting rule is given by Equation 2,

$$p_{t'}^i = E_{t'}^i(v_t) = v_t(1+\xi), \qquad \xi \in [-0.01, 0.01]. \tag{2}$$

[12]Sinolink Securities Special Reports for Stock Index Futures, 'Stock index futures lead stock index for 2 minutes and it contains multidimensional opportunities', 2010, China, in Chinese.

(2) An intelligent trader observes the $t-\tau$ period's fundamental value $v_{t-\tau}$ when he enters the market, he also make use of the average trading price $\bar{p}_{t,\tau}$ of the past τ periods and the bid-ask midpoint $p^m_{t'}$,

$$\bar{p}_{t,\tau} = \frac{1}{\tau}[p_{t-1} + p_{t-2} + \cdots + p_{t-\tau}], \qquad p^m_{t'} = \frac{1}{2}(a_{t'} + b_{t'}). \tag{3}$$

The forecasting rule of the intelligent trader i is given by

$$p^i_{t'} = E^i_{t'}(v_t) = \frac{1}{x^i_{t'} + y^i_{t'} + z^i_{t'}}(x^i_{t'} v_{t-\tau} + y^i_{t'} \bar{p}_{t,\tau} + z^i_{t'} p^m_{t'}), \tag{4}$$

where x, y, and z are forecasting coefficients. Intelligent traders optimize the coefficients by genetic algorithm. The value for x, y, and z are bounded between 0.01 and 0.99. Appendix C provides detailed discussions about the genetic algorithm.

(3) The forecasting rule for the simple trader is the same as intelligent trader except the values of x, y, and z are selected randomly between 0.01 and 0.99.

(4) The liquidity traders do not make any forecasts, they randomly selects to submit either buy or sell market orders meet their liquidity demand.

3.5. **Order Size under the position limit.** Position limit has great impact on order size. Obviously, traders cannot submit an order with size large than two times of the position limit[13]. There are two ways to determine the order size. One way is to employ a CARA risk preference utility to generate the demand of traders, see for example Chiarella, Iori and Perellò (2009), which has a theoretical foundation, but difficult to implement. Furthermore, it is unlikely that order size in actual markets is close to the theoretically optimal demand because, for example, high frequency traders usually break their trade into smaller sizes to minimize market impact and have zero net position at the end of each trading day, also liquidity traders need to implement their liquidity demand in one transaction for special requirements[14].

We model order size using the second way. In order to generate realistic order flow, we estimate a probability density function (pdf) of order sizes based on the empirical data on investors' order submissions[15]. The pdf of $|q^i_t|$ is given by

$$f^i(x) = \alpha^i e^{\beta^i x} + \gamma^i e^{\delta^i x}, \tag{5}$$

where $x \in (0, \infty)$ and α^i, β^i, γ^i and δ^i are the parameters for different type traders, respectively. We assume the order size for type i trader is i.i.d for each period. The pdf specified in equation (5) seems to best capture the empirical data. The fitted values for the parameters are presented in Table 4. According to the pdf $f^i(x)$, we

[13]We consider an extreme case, that is, when an investor has the maximum long position θ but wants to hold the maximum short position θ, so the sell order size is 2θ.

[14]For example, some index tracking funds need to adjust their position limit immediately.

[15]The data includes the 5-second high frequency market data and the account data in the CSI 300 futures market, from August 23, 2010 to September 15, 2010.

generate an order size $|q_t^i|$ for trader type i. The fitting maps of the pdf for the four types of investors are presented in Appendix D.

Investor type	α^i	β^i	γ^i	δ^i
Informed traders	0.2152	-0.2130	0.0016	-0.0081
Intelligent traders	0.8088	-0.7682	0.0511	-0.1107
Simple traders	5.1980	-2.1570	0.1077	-0.3107
Liquidity traders	9.1840	-2.4590	0.0916	-0.5296

TABLE 4. Parameters of investors' order-size probability-density function.

Note that the pdf $f^i(x)$ is not bounded above, therefore without a position limit, traders (especially the informed traders) can submit large orders (either buy or sell) that may lead to large price fluctuations. However, the introduction of a position limit θ truncates the distribution in the following way. Suppose a trader enters the market at time t and N number of his previous submitted order were executed, indexed by $n = 1, \cdots, N$, with sizes $|q_n^{i*}|$. We define trader i's current holding of futures contracts as

$$Q_t^i = \sum_{n=1}^{N} q_n^{i*}. \tag{6}$$

Since trader i's net holding cannot exceed θ, when trader i submits an order with size $|q_t^i|$ at time t, it must be that $|Q_t^i + q_t^i| \leq \theta$ which is equivalent to

$$-\theta - Q_t^i \leq q_t^i \leq \theta - Q_t^i.$$

Therefore, if trader i submits a buy (sell) order, $f^i(x)$ must be truncated at $x \leq \theta - Q_t^i$ ($x \leq -\theta - Q_t^i$).

3.6. **Order Submission Rules.** For order submission rules, we follow Gil-Bazo, Moreno and Tapia (2007) and Wei et al. (2013). If an investor's forecast $p_{t'}^i$ of the fundamental value significantly differs from the actual fundamental value v_t, and the expected order profit is more than the transaction cost μ, then the investor submits a market order, otherwise he submits a limit order. The bid-ask spread is denoted by $s_{t'} = a_{t'} - b_{t'}$, and the limit order price is denoted by p_l. The submission rules are presented in Table 5.

3.7. **Experiment design.** The experiments are based on prior empirical analysis outlined in Section 2. We set the position limit to 111, 181, 223 and 371 corresponding to the four states based on market illiquidity and tolerable price change of the regulator. We examine the impact of position limits on volatility, liquidity, and the efficiency of information-dissemination. Based on the results, we provide some policy implications. Since exchanges round of the position limits to hundreds, we

Scenario	Order
Case 1: There is at least one ask price and one bid price in the limited order book	
$p_{t'}^{i} > a_{t'} + \mu$	Market order to buy
$a_{t'} + \mu \geq p_{t'}^{i} \geq b_{t'} - \mu \,\&\, \lvert a_{t'} - p_{t'}^{i} \rvert \leq \lvert p_{t'}^{i} - b_{t'} \rvert$	Limit order to buy with $p_l = p_{t'}^{i} - \mu$
$a_{t'} + \mu \geq p_{t'}^{i} \geq b_{t'} - \mu \,\&\, \lvert a_{t'} - p_{t'}^{i} \rvert > \lvert p_{t'}^{i} - b_{t'} \rvert$	Limit order to sell with $p_l = p_{t'}^{i} + \mu$
$p_{t'}^{i} < b_{t'} - \mu$	Market order to sell
Case 2: There are no bid prices	
$p_{t'}^{i} > a_{t'} + \mu$	Market order to buy
$p_{t'}^{i} \leq a_{t'} + \mu$	Limit order to buy with $p_l = p_{t'}^{i} - \mu$
Case 3: There are no ask prices	
$p_{t'}^{i} < b_{t'} - \mu$	Market order to sell
$p_{t'}^{i} \geq b_{t'} - \mu$	Limit order to sell with $p_l = p_{t'}^{i} + \mu$
Case 4: There are no ask or bid prices	
With probability 50%	Limit order to buy with $p_l = p_{t'}^{i} - \mu$
With probability 50%	Limit order to sell with $p_l = p_{t'}^{i} + \mu$

Table 5. Order Submission Rules.

modify the position limits to 100, 200, 300, and 400, and we name the experiments Exp.1, Exp.2, Exp.3, and Exp.4 respectively. The position limit of Exp.1 is the same as the actual market, thus is referred to as the benchmark case.

Each experiment group runs 30 times with different random seeds to meet the statistical significance requirement. Each simulation runs for 51,876 periods based on the fundamental value of the CSI 300 futures calculated the given data. The first 37,446 periods (13 days) are used for the intelligent traders to learn and optimize the forecasting rules, the results are based on the remaining 14,430 periods (5 days).

4. The market quality analysis

The optimization of position-limit settings aims to improve market quality, which mainly relies on three market-quality indicators: market liquidity represented by transaction volume, order book depth and the bid-ask spread; pricing efficiency represented by information dissemination and the forecasting accuracy of the uninformed traders; and market volatility represented by the standard deviation of the market price return (per period) and the instantaneous price change. The trading welfare for each type of trader is measured by their average order profit. We also report the the simulated market price, order book and the trading volume in the Appendix E, the results show that the model generates some of the stylized facts of the CSI 300 futures market.

4.1. **Liquidity.** We first examine *trading volume* since a higher trading volume would result in a larger commission for the exchange. We use Analysis of variance (ANOVA) to analyze sample differences among the experiment groups. Figure 5 shows a sharp increase of trading volume of 15.23% when position limit θ increases from 100 to 200, we observe a further increase of 4.34% when θ increases from 200 to 300, then no significant changes when θ increases from 300 to 400.

Next, we examine the change in *order depth*. We focus on order depth at the best quotes. Figures 2(a) and 2(b) show that when the position limit θ increases from 100 to 200, order depth increases by more than 30%, then more than 10% from 200 to 300, lastly less than 5% from 300 to 400.

Furthermore, Figure 3 indicates that the *bid-ask spread* becomes slightly wider (though not statistically significant) when position limit increases from 100 to 200, and then no significant changes when position limit further increases.

Table 6 shows that the change in liquidity is mainly due to the orders submitted by the informed traders. Results show that when position limit increases, informed traders submit more limit orders and market orders, also a larger proportion of the limit orders are executed. In contrast, we do not see similar changes for other types of traders. Furthermore, according to Table 6, when position limit increases, informed traders submit much more limit orders than market orders, thus they are providing liquidity rather than consuming liquidity, which is consistent with the increase in order depth. Also, a larger proportion of the limit order submitted are executed, which explains the increase in trading volume.

4.2. **Information efficiency.** The information efficiency reflects the pricing efficiency, which is a core indicator of the market quality. We use the *mean absolute error* (MAE) between market price and the fundamental value proposed by Theissen (2000) to measure the convergence of the market price to the fundamental value, which reflect market's information efficiency. The MAE is defined as

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |p_t - v_t|. \tag{7}$$

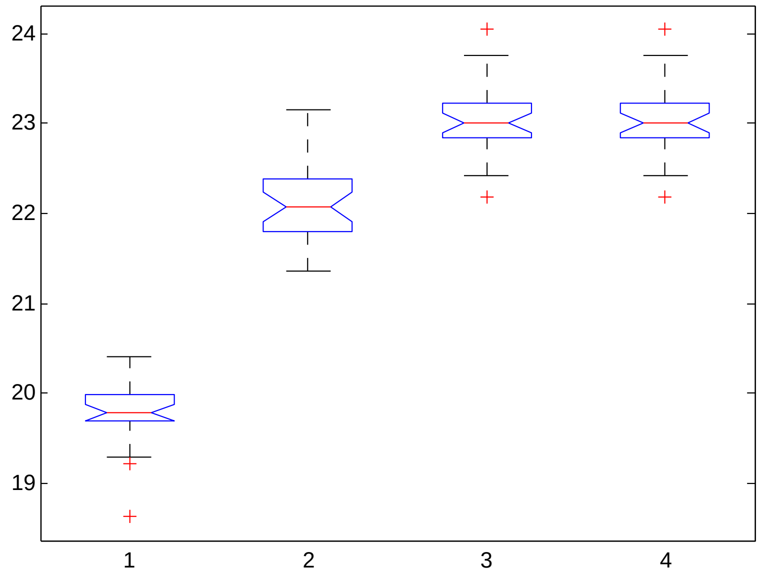
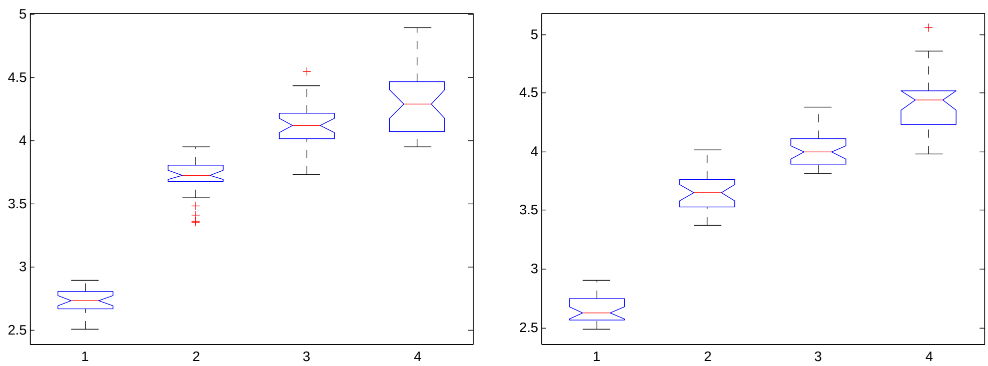


FIGURE 1. The ANOVA of trading volume. The p value is less than 1%.



(a) Depth at bid. (b) Depth at ask.

FIGURE 2. The ANOVA of depth at bid and ask. The p value of figure 2(a) and 2(b) are less than 1%.

Similarly, we define the mean absolute deviation (MAD) to measure the forecasting errors of intelligent traders (who use GA learning) and simple traders.

$$MAD_i = \frac{1}{T}\sum_{t=1}^{T} |p_t^i - v_t|. \qquad (8)$$

Figure 4 shows that MAE, MAD_{GA} and MAD_S all decrease with the position limit, implying that there is an improvement of information efficiency. Moreover, the increase in information efficiency is statistically significant when position limit increases from 100 to 200, and also from 200 to 300.

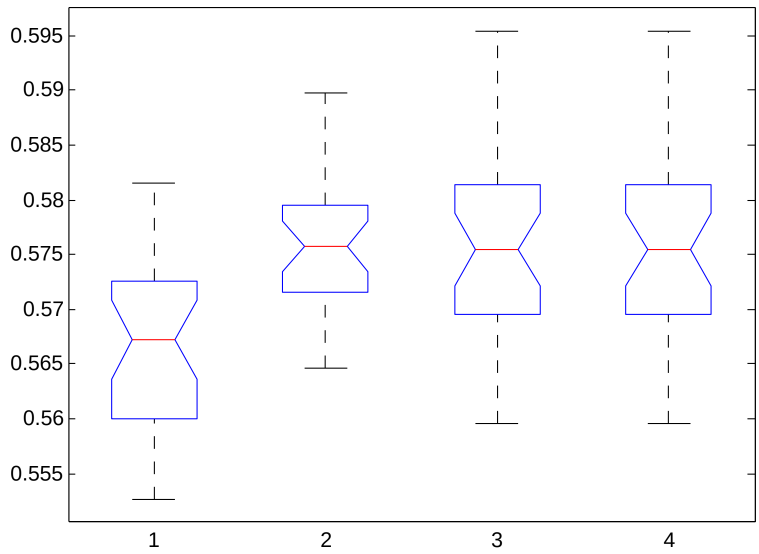


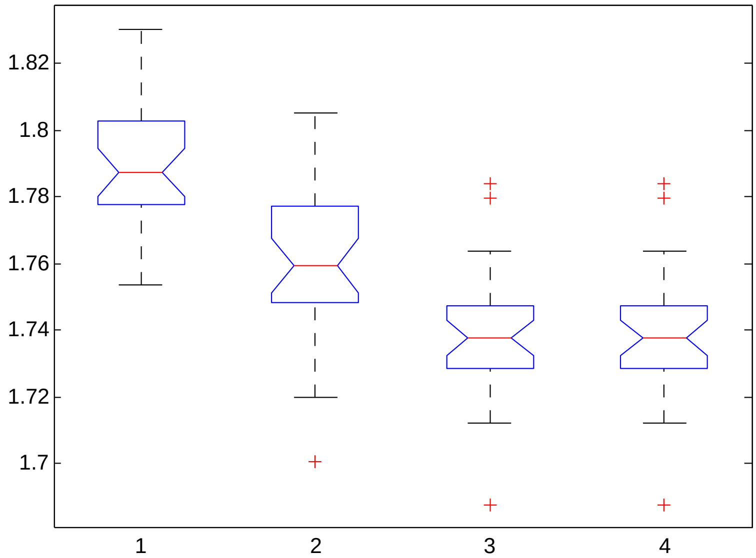
FIGURE 3. The ANOVA of bid-ask spread. The p value is less than 1%.

Exp.	*ILO*	*IMO*	*ILE*	*GALO*	*GAMO*	*GALE*	*SLO*	*SMO*	*SLE*	*LMO*
1	435,173	160,838	63,764	305,335	12,384	23,208	2,345,139	109,008	202,814	3,281
2	706,961	202,329	96,711	323,998	12,480	25,029	2,361,872	100,682	201,257	3,277
3	827,075	219,762	111,447	333,148	12,257	25,777	2,358,265	97,468	199,663	3,253
4	899,885	233,725	122,185	336,724	12,390	26,253	2,362,954	94,027	199,152	3,269

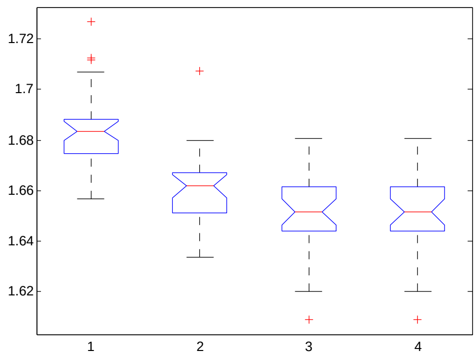
TABLE 6. *ILO*, *GALO*, and *SLO* denote the average number of limit orders submitted for the informed, intelligent and simple traders respectively. Similarly, *IMO*, *GAMO*, *SMO*, and *LMO* denote the average number of market orders submitted for the three types of traders, and *ILE*, *GALE*, and *SLE* denote the average number of submitted limit orders that are executed for the three types of traders.

This result is mainly driven the fact that an increase in the position limit motivates the informed traders to trade more aggressively, which helps to release information about the true fundamental value more quickly to the intelligent traders.

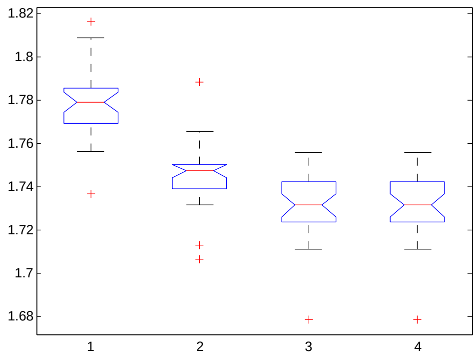
4.3. **Volatility.** We use the standard deviation of return of transaction prices to measure volatility. As shown in Figure 5, volatility increases in the position limit θ, which is most significant when θ increases from 100 to 200, from approximately 11.175 basis point (bp) to over 12.25 bp, which is a proportional increase of 6.4%. There are no significant changes to volatility when θ further increases to 300 or 400. Intuitively, volatility increases because informed traders trade more aggressively and submit a larger number of market orders, which actually improve the dissemination of information about the fundamental value. Therefore, the increase in volatility should not be interpreted as a deterioration of market quality, instead it shows that



(a) MAE.



(b) MAD_{GA}.



(c) MAD_S.

FIGURE 4. The ANOVA of information dissemination indicators. MAD_{GA} is the MAD of intelligent traders, and MAD_S is the MAD of simple traders. The p value of figure 4(a), 4(b) and 4(c) are less than 1%.

increasing the position limit helps the observed prices to better reflect informational about fundamentals, thus improve market efficiency.

An important concern from the market regulator's point of view is whether instantaneous price changes are under control. Based on Dutt and Harris (2005)'s model, instantaneous price change is an increasing function of the position limit set by the regulator, because it gives more incentives for manipulative trades in the spot market. However, our simulation results show that instantaneous price changes in the futures market are never above 2% regardless of whether position limit is set to 100, 200, 300 or 400. There are times when instantaneous price changes are above the 1% tolerance level. We calculate the average number of times when price changes

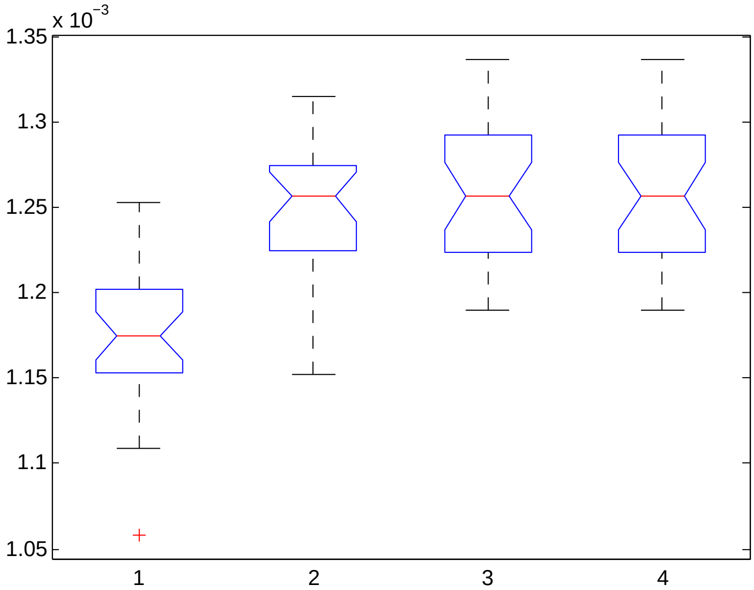


FIGURE 5. The ANOVA of standard deviation of market price return. The p value is less than 1%.

are larger than 1% over 30 simulations. Figure 6 shows that the average number of times when instantaneous price changes exceeds 1% does not change significantly as position limit increases. Intuitively, although increasing the position limit allows informed traders the possibility to submit large market orders, however from Table 6 we see that informed traders actually submit a larger of limit orders compare to market orders, which increases the order depth at the best bid and ask. Therefore, it seems likely that the larger market orders submitted by some of the informed traders are absorbed by larger limit order submitted by the other informed traders.

4.4. **Trading welfare.** Lastly, we turn to the order profits for the four types of traders under different position limits. The order profit of an executed order is measured by $r_t = p_t - v_t$ for a sell order and $r_t = v_t - p_t$ for a buy order. We use r_I, r_{GA}, r_S, r_L to denote the average profit per order (order size not considered) for the informed, intelligent, simple and liquidity traders respectively. Moreover, we use R_I, R_{GA}, R_S and R_L to denote the total profit for the four types of traders respectively, taking order sizes into consideration. Table 7 shows that the per order profits decrease for both informed and intelligent traders, however informed traders' total profit increase while intelligent traders' total profit decease. Intuitively, when position limit increases, informed traders submit larger orders, which leaks private information to the intelligent traders who use GA trying to extract from market information the correct fundamental value. However, the intelligent traders' learning is contaminated by the orders submitted by the simple traders (liquidity traders

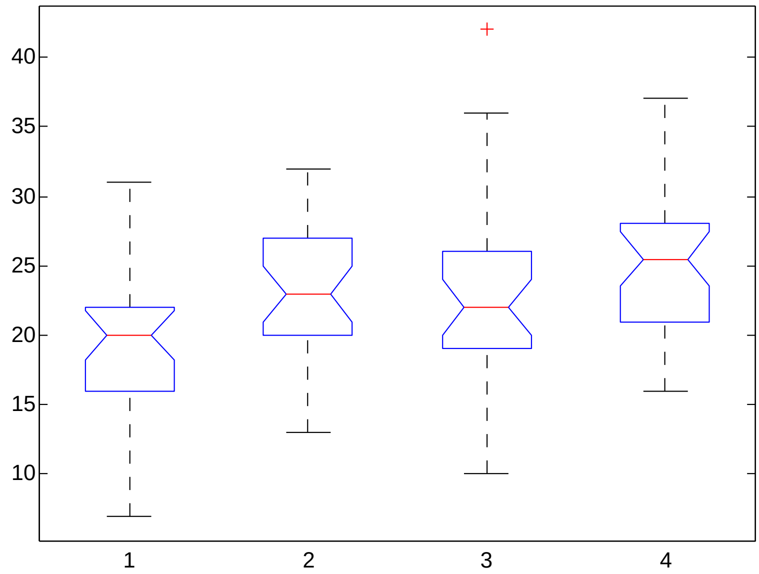


FIGURE 6. The ANOVA of the average number of that the absolute price change of one period (5 seconds) is more than 1%. The p value is less than 1%.

are largely irrelevant because they only enter the market once a day). Therefore, although the orders submitted by the informed traders becomes less profitable (per futures contract) as they submit larger orders, their total profit increases, and the additional profit gained largely come from the intelligent traders since the per order and total profits do not change significantly for the simple and liquidity traders. Therefore, increasing the position limit can potentially attract more informed traders (or institutional investors) to participate in the CSI futures market to compete for the additional profits.

Exp.	r_I	r_{GA}	r_S	r_L	R_I	R_{GA}	R_S	R_L
1	0.6572	0.5900	-0.5383	-0.2595	147,590	21,029	-167,766	-852
2	0.5660	0.4112	-0.6092	-0.2546	169,218	15,447	-183,830	-835
3	0.5352	0.3356	-0.6371	-0.2624	177,229	12,825	-189,200	-854
4	0.5172	0.2532	-0.6584	-0.2798	184,025	9,782	-192,892	-915

TABLE 7. The order profit of four types traders. r is the order profit per unit, R is the total order profit of each type traders.

5. CONCLUSION AND POLICY IMPLICATIONS

The paper uses an agent-based model with four investor types to examine the impact of increasing the position limit on market quality for the CSI 300 futures market. The informed traders know the fundamental value whereas the intelligent traders attempt to learn about the fundamental value from market information employing a genetic algorithm. Moreover, the simple traders do not learn and simply try to guess the fundamental value from lagged-fundamental value and past prices. Lastly, the liquidity traders randomly supply and demand liquidity from the market. The four investor types are realistically identified using the trading frequency and order return data from the CSI 300 futures market. Our model is designed to mimic all the important features of the actual market. Most importantly, we use the empirical distribution of the sizes of the orders submitted to CSI 300 futures market to determine the order size for each of the four investor types.

We find that increasing the position limit helps to improve market quality. Simulated results show that when the position limit increases from 100 to 300 trading volume increases by more than 20%, order depth increases by 30% at the best quotes. Although the bid-ask spread increases slightly, the increase is not statistically significant. Information dissemination improves as market prices converge closer to the fundamental value. Standard deviation of market price returns increases by 8.2 bp per period when position limit increases from 100 to 300, however we argue that this is sign that market prices are better reflecting information about the fundamentals rather than a deterioration in market quality. When the position limit increases further from 300 to 400, there is no significant changes to market quality.

Of course, we recognize that investors' behaviour such as their trading frequency, trading strategy and the distribution of their order sizes are likely to evolve and adapt to the increasing level of position limit in the CSI 300 futures market. The assumption that these elements remains the same may not be innocuous when the position limit increases by too much. Therefore, we recommend the regulator to first increase the position limit from 100 to 300 and monitor the market to see whether market quality indeed improves significantly as our model suggests, and after enough data have been gathered, one can re-simulate the agent-based model with updated parameter values (estimated from newly observed market information) so that the regulators can make a better informed decision of whether to further increase the position limit to 300 to a higher level.

Appendix

A. Derivation of prudent position limits in the CSI 300 futures Market. Following Dutt and Harris (2005), we derive the prudent position limits in the CSI 300 futures Market. Assuming that the underlying component price is a linear function[16] with its true value and trading quantity as Equation A.1, where P_i is the price associated with the ith underlying index component, and V_i is its true value,

[16]Dutt and Harris (2005) point out that the linear price function is widely accepted by market microstructure theory, as Kyle (1985) provides a seminal analysis.

and Q_i is the aggregate trading quantity of the manipulators in the underlying market. λ_i is a measure of the illiquidity of the underlying market.

$$P_i = V_i + \lambda_i Q_i. \tag{A.1}$$

The CSI 300 index I consisting of 300 underlying components, is denoted by

$$I = \frac{1000 \sum_{i=1}^{300} \omega_i g_i P_i}{D}, \tag{A.2}$$

where ω_i means the proportion of the tradable shares[17] of the ith component stock, g_i is the share factor, and D is the sum of the value-weighted constituent stocks capitalization in the initial period. The value of a contract is mI , m is the contract multiplier[18] for the cash settlement. Let θ be the number of contracts that the traders holds. The notional value Z of the traders contract position is

$$Z = \theta m I = \frac{\theta m}{D} \sum_{i=1}^{300} \omega_i g_i P_i = \frac{1000\theta m}{D} \sum_{i=1}^{300} \omega_i g_i (V_i + \lambda_i Q_i). \tag{A.3}$$

The trading cost of manipulation per component C_i is

$$C_i = (V_i + \lambda_i Q_i) Q_i + c_i Q_i - V_i Q_i = \lambda_i Q_i^2 + c_i Q_i, \tag{A.4}$$

where c_i is a per-share commission rate. So that the total cost to manipulate the underlying index is

$$C = \sum_{i=1}^{300} (\lambda_i Q_i^2 + c_i Q_i). \tag{A.5}$$

The net profit from the manipulation is

$$\Pi = Z - C = \frac{1000\theta m}{D} \sum_{i=1}^{300} \omega_i g_i (V_i + \lambda_i Q_i) - \sum_{i=1}^{300} (\lambda_i Q_i^2 + c_i Q_i). \tag{A.6}$$

Maximizing Equation A.6 with respect to Q_i yields the profit-maximizing quantity for all underlying components, as show in Equation A.7:

$$Q_i = \frac{500\theta m \omega_i g_i}{D} - \frac{c_i}{2\lambda_i}. \tag{A.7}$$

Substituting Equation A.7 into Equation A.1, we get the percentage of price change due to manipulation:

$$\frac{P_i - V_i}{V_i} = \frac{500\lambda_i \theta m \omega_i g_i}{D V_i} - \frac{c_i}{2V_i}. \tag{A.8}$$

[17] In Chinese stock markets, shares are divided into two parts. One part is non-tradable share, most of the owners are government entities, so-called “state shares”; the other is tradable shares which hold by normal shareholders. Most of the CSI 300 components have about 2/3 non-tradable shares.

[18] The value of a contract calling for the cash settlement of m times the value of the index, m is equal to 300 for CSI 300 index futures.

We define an elasticity ε_i of price with respect to the fraction of all outstanding shares traded by the manipulator. Let

$$\varepsilon_i = \frac{\lambda_i Q_i/V_i}{Q_i/S_i} = \frac{\lambda_i S_i}{V_i}, so \qquad \lambda_i = \frac{\varepsilon_i V_i}{S_i}. \tag{A.9}$$

Substituting Equation A.9 to Equation A.8 yields

$$\frac{P_i - V_i}{V_i} = \frac{500\theta m\omega_i g_i \varepsilon_i}{DS_i} - \frac{c_i}{2V_i}. \tag{A.10}$$

We choose the absolute capitalization-weighted average percentage price change for the index stocks as the tolerable price change $k\%$. We let $\psi_i = \frac{S_i V_i}{\sum_{j=1}^{300} S_j V_j}$ be the capitalization-value-weight of the ith component stock. So the price change no more than $k\%$ is expressed as

$$\sum_{i=1}^{300} \psi_i \frac{P_i - V_i}{V_i} = \sum_{i=1}^{300} \psi_i (\frac{500\theta m\omega_i g_i \varepsilon_i}{DS_i} - \frac{c_i}{2V_i}) \leq k. \tag{A.11}$$

So that the prudent position limit of CSI 300 futures is

$$\theta^* = \frac{DK}{500m\sum_{i=1}^{300} \psi_i \omega_i \varepsilon_i (g_i/S_i)} + \frac{D\sum_{i=1}^{300} \psi_i (c_i/2V_i)}{500m\sum_{i=1}^{300} \psi_i \omega_i \varepsilon_i (g_i/S_i)}. \tag{A.12}$$

Because c_i is very small relative to V_i , so the second term of Equation A.12 does not matter much, and the CSI 300 index is a value-weighted index, so that $g_i = S_i$ and all ε_i can be assume to a constant value ε[19], so the Equation A.12 reduces to Equation 1 int the section 2 as follow:

$$\theta^* = \frac{DK}{500m\varepsilon\sum_{i=1}^{300} \psi_i \omega_i}.$$

B. Derivation of the ceiling of the risk-free, cash-and-carry arbitrage. We assume that if there is no arbitrage opportunity, the sum of cash flows of underlying stocks and the CSI 300 futures from time t to T are equal to zero. We define the variance as in Table A.1. Then we show the detail of cash flow in Table A.2.

As the sum of cash flow at time t is zero, the cash-and-carry arbitrage will be a success when the sum of cash flow at time T is greater than zero. Assuming that holding the positron due to futures maturity time T , we let $S_t = S_T = F_T$, and determine that the ceiling of no arbitrage range is:

$$S_T - S_T C_{sT} - S_T C_{si} + d - (S_t + S_t C_{st} + S_t C_{si})(1+r)^{(T_d - t_d)/365} +$$
$$F_t - F_T - F_T C_{fT} - F_T C_{fi} + F_t e - (F_t e + F_t C_{ft} + F_t C_{fi})(1+r)^{(T_d - t_d)/365} = 0 \tag{A.13}$$

[19]Dutt and Harris (2005) set it to 150. The component stocks of the CSI 300 are large stocks and have stable liquidity, so we also assume ε_i to be a constant value.

Parameter	Setting	Note	Parameter	Setting	Note
t_d		The trading day at time t	T_d		The trading day at time T
S_t	Imported from the real market	The price of the CSI 300 index at time t	S_T		The price of the CSI 300 index at time T
F_t		The price of the CSI 300 futures at time t	F_T		The price of the CSI 300 futures at time T
C_{ft}	0.005%	Commission for trading futures	C_{fT}	0.01%	Handling fees for delivery
C_{st}	0.02%	Handling fees for buying stocks	C_{sT}	0.12%	Handling fees for selling stocks
C_{si}	0.21%	Impact cost of stocks	C_{fi}	0.015%	Impact cost of futures
r	6%	Annual risk-free interest rate	e	15%	Margin ratio
d	4.1495	The sum of all dividends from time t to time T by compounding interest			

TABLE A.1. The definition of parameters

Items	Cash Flow at day t_d	Cash Flow at day T_d
	Stocks	
Buying stocks	$-S_t$	
Cost of buying stocks	$-S_tC_{st} - S_tC_{si}$	
Finance for buying stocks	$S_t + S_tC_{st} + S_tC_{si}$	
Selling stocks		S_T
Cost of selling stocks		$-S_TC_{ST} - S_TC_{Si}$
Dividends		d
Paying back the initial lending money		$-(S_t + S_tC_{st} + S_tC_{si}) \times (1+r)^{(T_d - t_d)/365}$
	Futures	
Margin of selling futures	$-F_te$	
Cost of selling futures	$-F_t \times C_{ft} - F_tC_{fi}$	
Finance for selling futures	$F_te + F_tC_{ft} + F_tC_{fi}$	
Profit of closing position		$F_t - F_T$
Cost of trading futures		$-F_TC_{fT} - F_TC_{fi}$
Recovering margin		F_te
Paying back the initial lending money		$-(F_te + F_tC_{ft} + F_tC_{fi}) \times (1+r)^{(T_d - t_d)/365}$

TABLE A.2. Cash flows for the risk-free cash-and-carry arbitrage.

Substituting $S_t = S_T = F_T$ into the Equation A.13, we can determine the ceiling F_t^* as the fundamental value v_t as follow:

$$v_t = F_t^* = \frac{S_T(C_{sT} + C_{si} + C_{fT} + C_{fi}) + S_t(1 + C_{st} + C_{si})(1+r)^{(T_d - t_d)/365} - d}{1 + e - (e + C_{ft} + C_{fi})(1+r)^{(T_d - t_d)/365}}. \tag{A.14}$$

So if the CSI 300 futures market price F_t is higher than v_t, traders can do the risk-free cash-and-carry arbitrage and get positive profit.

C. Genetic Algorithm (GA). We introduce the details of the implementation of the genetic algorithm (GA) of the intelligent traders. We use GA to optimize the intelligent traders' forecasting. The GA with classifier system is revised from the typical GA of the SFI-ASM (Santa Fe Institution Artificial Stock Market, see Arthur, Holland, LeBaron, Palmer and Tayler (1997) and Ehrentreich (2008) for details). The key task of applying the GA of SFI-ASM to the ACFM is in using a classifier system to describe the market conditions of the ACFM. Unlike the SFI-ASM which uses a specialist for market cleaning so as to make the market conditions simple, the ACFM employs a continuous double auction to match orders that make the market conditions more complex. We redesign a classifier system and let it use some rules similar to technical analysis based on the fundamental value $v_{t-\tau}$, the current bid-ask midpoint $p^m_{t'}$, and the average historical price $\bar{p}_{t,\tau}$. All the classified rules are showed in the Table A.3. The forecasting rule contains two parts, one part is the condition part, which describes the using condition by classified system rules, and the forecasting part is constructed by the three parameters x, y and z in Equation 4. There are 60 forecasting rules in total. When the intelligent trader i enters the market, the forecasting rule whose condition part matches the current market condition is selected to the candidate list. Then the trader chooses the best forecasting rule which has highest historical performance. If no forecasting rule matches the current market condition, the GA generate a new rule which condition part is set to match the current market condition and the forecasting part is set randomly. Then, the trader use three parameters x, y, and z in the forecasting part to forecast the current fundamental value according to Equation 4. In brief, genetic algorithm use an evolution process including selection, crossover, and mutation to optimize the forecasting rules of intelligent traders. The evolution process of genetic algorithm is active every 120 periods. When the evolution process is active, the selection process orders the forecasting rules according to their historical performances, and the crossover and mutation processes generate a number of new forecasting rules from the rules which have high historical performances with an exogenous probability[20]. The evolution process changes both the market condition part and the forecasting part of the forecasting rule. Then the GA uses the new forecasting rules to replace some old rules with low historical performances[21]. We refer to Wei et al. (2013) for the details of the GA in limit order markets.

D. Fitting maps of the order-size probability-density functions for four types investors . Using the account data of order submission, we use Matlab to generate the order-size probability-density functions for four types traders as showed in Equation 5. The fitting maps are showed in Figure A.1 and the Goodness-of-fit coefficients are showed in Table A.4.

[20]The crossover rate is set to 0.1 and the mutation rate is set to 0.3.

[21]The replace rate is set to 10%.

Number	Rule	Number	Rule	Number	Rule
1	$p_{t'}^{m} / \overline{p}_{t,\tau} > 0.90$	10	$\overline{p}_{t,\tau} / v_{t-\tau} > 0.90$	19	$\overline{p}_{t,\frac{\tau}{2}} > \overline{p}_{t,\tau}$
2	$p_{t'}^{m} / \overline{p}_{t,\tau} > 0.93$	11	$\overline{p}_{t,\tau} / v_{t-\tau} > 0.93$	20	$\overline{p}_{t,\frac{\tau}{4}} > \overline{p}_{t,\frac{\tau}{2}}$
3	$p_{t'}^{m} / \overline{p}_{t,\tau} > 0.95$	12	$\overline{p}_{t,\tau} / v_{t-\tau} > 0.95$	21	$\overline{p}_{t,\frac{\tau}{6}} > \overline{p}_{t,\frac{\tau}{4}}$
4	$p_{t'}^{m} / \overline{p}_{t,\tau} > 0.97$	13	$\overline{p}_{t,\tau} / v_{t-\tau} > 0.97$	22	$\overline{p}_{t,\frac{\tau}{12}} > \overline{p}_{t,\frac{\tau}{6}}$
5	$p_{t'}^{m} / \overline{p}_{t,\tau} > 1$	14	$\overline{p}_{t,\tau} / v_{t-\tau} > 1$	23	$\overline{p}_{t,\frac{\tau}{2}} > v_{t-\tau}$
6	$p_{t'}^{m} / \overline{p}_{t,\tau} > 1.03$	15	$\overline{p}_{t,\tau} / v_{t-\tau} > 1.03$	24	$\overline{p}_{t,\frac{\tau}{4}} > v_{t-\tau}$
7	$p_{t'}^{m} / \overline{p}_{t,\tau} > 1.05$	16	$\overline{p}_{t,\tau} / v_{t-\tau} > 1.05$	25	$\overline{p}_{t,\frac{\tau}{6}} > v_{t-\tau}$
8	$p_{t'}^{m} / \overline{p}_{t,\tau} > 1.07$	17	$\overline{p}_{t,\tau} / v_{t-\tau} > 1.07$	26	$\overline{p}_{t,\frac{\tau}{12}} > v_{t-\tau}$
9	$p_{t'}^{m} / \overline{p}_{t,\tau} > 1.10$	18	$\overline{p}_{t,\tau} / v_{t-\tau} > 1.10$		

Table A.3. Classified Rules.

Investor type	SSE	R-square	Adjusted R-square	RMSE
Informed traders	0.002758	0.9666	0.9655	0.00536
Intelligent traders	0.001149	0.9951	0.995	0.00346
Simple traders	0.0005317	0.9989	0.9988	0.002353
Liquidity traders	3.58E-05	0.9999	0.9999	0.0006105

Table A.4. Goodness-of-fit coefficients of the order-size probability-Density Functions for four types traders.

E. The observation of market price, order book and trading volume. Here we provide some observation results from one typical simulation of the Experiment 1. Figure A.2 shows prices' dynamics of the whole recorded periods. The market price p_t has a consistent trend and similar fluctuated shape with the CSI 300 futures price $p_{IF^{1009}}$. Figure A.3 illustrates one period's limit order book, which shape is similar with realistic. Figure A.4 shows that the trading volume fluctuates like the real market volume dynamics. These figures intuitively show that the ACFM can generate realistic features of the CSI 300 futures market.

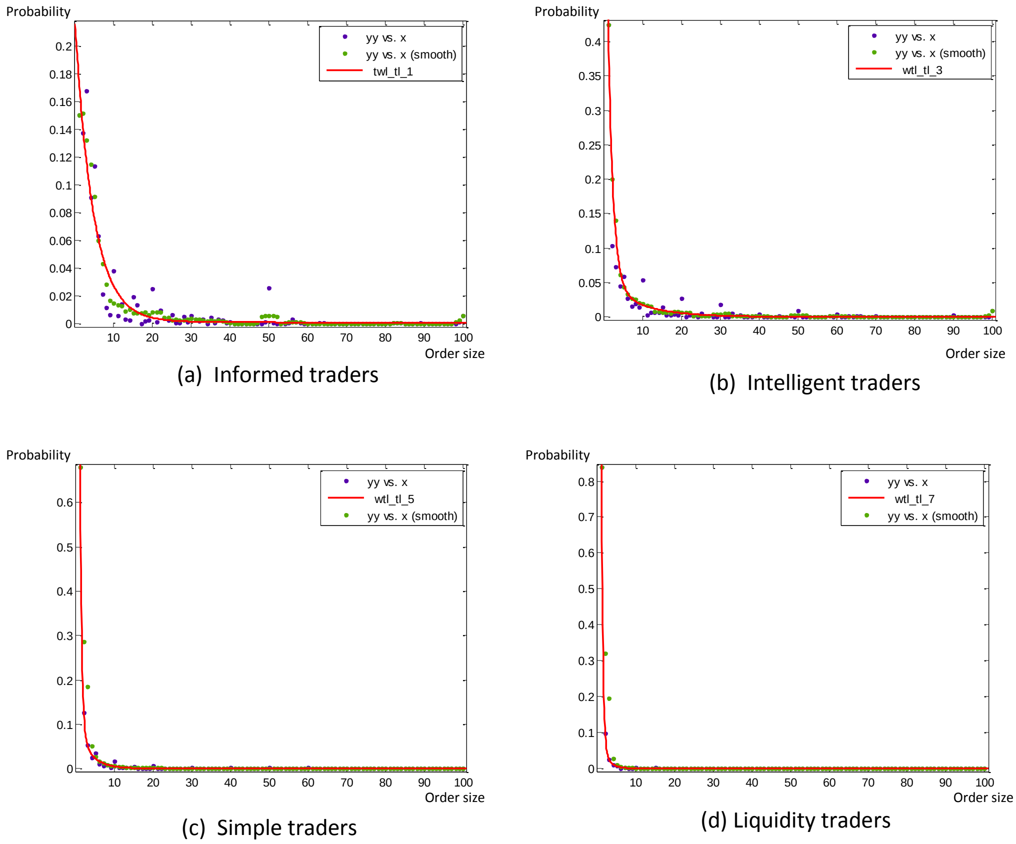


FIGURE A.1. The fitting maps of the order-size probability-density functions for four types traders .

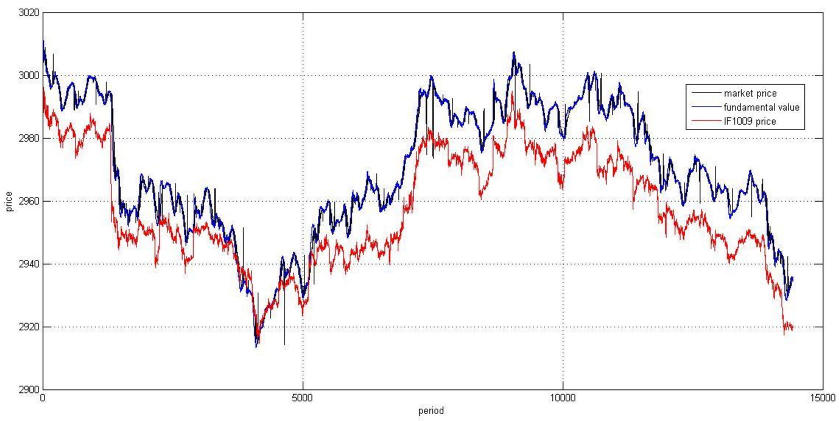


FIGURE A.2. Price chart of market price, fundamental value, and the real CSI 300 stock futures price in the whole recorded periods.

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Figure A.3. The order book dynamics of the Experiment 1.

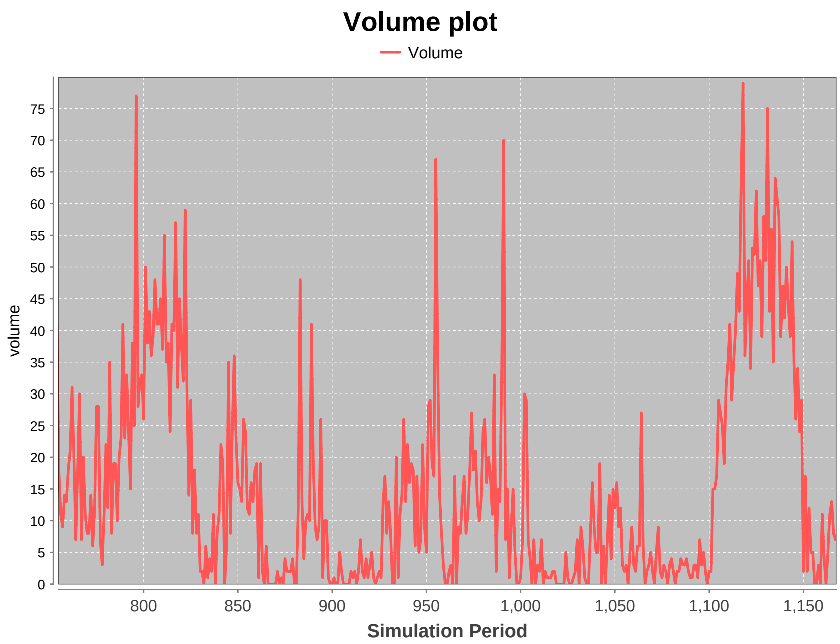

Figure A.4. The volume plot of the Experiment 1.

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